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## Optimal LQG Controller for Variable Speed Wind Turbine Based on Genetic Algorithms

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### Abstract

Linear Quadratic Gaussian (LQG) control methodology shows useful properties of good performance and robustness in controller design applied to wind turbine. Typically, in the design procedure LQG method is necessary to select weighting matrices in order to solve the Algebraic Riccati Equations and then get the matrices Kalman Filter gain and optimal state-feedback. In order to optimize a LQG control applied to Double-Fed Induction Generator in wind power system, a Genetic Algorithms (GA) adapted to get the best values of the element of weighting matrices is proposed in this paper. The performance indices ISE and ITSE are a good alternative to obtain the fitness function to design LQG controllers with GA. The simulation results show the high effectiveness of this optimal design method.

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**Keywords:** LQG controller, double fed induction generator, wind turbine, genetic algorithm, performance index

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### 1. Introduction

Many controllers for regulating the active and reactive power delivery in Double-Fed Induction Generators (DFIG), for wind power applications, are based in Linear Quadratic Gaussian (LQG) control methodology. That type of control shows useful properties of good performance and robustness in controller design applied to wind energy converters system [1]. Although the application of LQG control for DFIG wind turbines is not new, recent research report using LQG controllers successfully [2, 3, 4, 5].

In typical LQG control design, the designer will test with different weighting matrices so that the performance and robustness requirements are achieved. The parameters of the weighting matrices are usually adjusted manually by trial and error method. Some methods for selecting the initial point of iteration of the weighting matrices are suggested in the literature [6, 7, 8, 9]. For example, one method is using Bryson's rule [7], which scales the variables that appear in the function of cost, so that the maximum acceptable value for each term is one. However, none of these methods ensures the optimal selection of weighting matrices and usually several iterations must be performed to find matrices that meet the specified requirements [10].

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This manual selection of the elements of the matrices is not straightforward and therefore Evolutionary Algorithms such as Genetic Algorithms (GA) can be used to automate the search for the best values of the weighting matrices that meet design specifications.

The LQG methodology is based on a general methodology that is called Linear Quadratic (LQ). That approach determines state-feedback gains so that the closed-loop system optimizes a cost function. In fact, Linear Quadratic Regulator (LQR) technique is considered the groundwork of the LQG methodology of robust control systems. Artificial intelligence techniques have been applied to obtain the weighting matrices in LQR design. For example, da Fonseca *et al.* [10] presented the synthesis of the LQR control design problem and combined two computation intelligence paradigm to solve that problem, GAs to perform the search of the weighting matrices and the recurrent artificial neural network to perform the Algebraic Riccati Equation solution.

Mei and Goodal [11] present control strategies for active steering of solid axle railway vehicles using the LQG method, which used a GA to search for the best values for one of the two weighting matrix of LQG design, the other one is manually set based on empirical approach. Recently, Zhang *et al.* [12] have reported a LQG with loop transfer recovery flight controller optimal design method based on differential evolution algorithm. Four different weighting matrices have been adjusted in order to get the flying quality requirement and the robustness.

In order to optimize a control applied to DFIG in wind power system, a control structure based on LQG methodology and a GA adapted to get the best values of element of weighting matrices is proposed in this paper.

## 2. System Modeling

The study presented in this paper has been carried out for wind turbine of horizontal axis three-blade with double fed induction generator DFIG connected to the electricity distribution network. A control of active power, reactive power and rotor angular velocity has been applied in order to maintain the nominal steady state operation of the system under typical variation of the wind speed. This section is dedicated to the dynamic models of the components of the proposed wind turbine system. This includes wind speed, aerodynamic, mechanical and induction machine models.

### 2.1. Wind Speed Model

The wind speed model proposed by Carvalho [13] is used in this paper. Carvalho [13] introduces the wind speed as the sum of two components: deterministic and stochastic components. Deterministic component is the mean wind speed, which is considered constant in a period of short duration, typically less than 10 minutes. Stochastic component, called turbulence, represents the time variant part of the wind speed acting on the rotor area. The Kaimal spectrum is used to depict stochastic component in frequency domain. The turbulence is simulated by interconnect a white noise generator to a filter, which shows a Power Spectrum Density (PSD) similar to Kaimal spectrum. In addition, a third harmonic and dc component filters have been connected to represent the fluctuations on aerodynamic torque. A detailed description of that model can be consulted in [13, 14].

### 2.2. Wind Turbine Aerodynamics

Wind turbine aerodynamic model is based on Rankine-Froude disc actuator model. The aerodynamic power developed in the wind turbine is given by:

$$P_a = \frac{1}{2} \cdot \rho \cdot A \cdot V_w^3 \cdot C_p(\lambda, \beta) ; \quad \lambda = \frac{\omega_R \cdot R}{V_w} \quad (1)$$

Where  $\rho$  is the air density,  $A$  is the rotor surface,  $V_w$  is the wind speed,  $C_p$  is the power coefficient,  $\beta$  is the blade pitch angle,  $\lambda$  is the tip speed ratio,  $\omega_R$  is the angular speed of the turbine shaft and  $R$  is the rotor radius. The power coefficient depends of aerodynamic turbine design and his value never is greater than a theoretical maximum value of 0.593, called Betz limit. Because an expression to  $C_p$  required complex and

extensive aerodynamic knowledge, different numeric approximations have been developed. In this study, the expression  $C_p$  is approximated analytically according to 2, which is proposed by Heier [15].

$$C_p = 0.5176 \cdot (116\lambda_i^* - 0.4\beta - 5) \cdot e^{-21\lambda_i^*} + 0.0068\lambda ; \quad \lambda_i^* = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \quad (2)$$

The aero torque is calculated by:

$$T_a = \frac{P_a}{w_R} \quad (3)$$

Equations 1 to 3 give a model for the transfer of wind kinetic energy to mechanical energy on the shaft of wind turbine.

### 2.3. Mechanical Model

The mechanical transmission system of horizontal axis wind turbine includes the blades, low speed shaft, gear box, high speed shaft and generator. A three-mass equivalent model has been used to represent the dynamic of this system. The equations 4 - 6 depict the system dynamic taking in account the stiffness and damping coefficient of low and high speed shaft.

$$J_R \frac{dw_R}{dt} = T_a - D_R (w_R - w_1) - k_R \quad J_1 \frac{dw_1}{dt} = D_R (w_R - w_1) + k_R - T_1 \quad (4)$$

$$J_2 \frac{dw_2}{dt} = T_2 - D_g (w_2 - w_g) - k_g \quad J_g \frac{dw_g}{dt} = D_g (w_2 - w_g) + k_g - T_g \quad (5)$$

$$\frac{dk_g}{dt} = K_g (w_2 - w_g) \quad \frac{dk_R}{dt} = K_R (w_R - w_1) \quad \frac{T_1}{T_2} = \frac{w_2}{w_1} = n_{gb} \quad (6)$$

Where  $w_R$ ,  $w_g$ ,  $w_1$ ,  $w_2$  are the turbine, generator and gear boxes angular speed,  $J_R$ ,  $J_g$ ,  $J_1$ ,  $J_2$  are the turbine, generator and gear boxes moment of inertia,  $T_a$ ,  $T_g$  are the aerodynamic and electromagnetic torque,  $K_R$ ,  $K_g$  are the low and high speed shaft torsional stiffness,  $D_R$ ,  $D_g$  are the low and high speed shaft damping coefficient and  $n_{gb}$  is the gearbox ratio.

### 2.4. Double-Fed Induction Generator (DFIG)

The mathematical model of the DFIG used in this paper is based on the  $d$ - $q$  synchronous reference frame. The equation 7-10 present a state space model based on the currents components (stator and rotor).

$$\frac{d}{dt} \begin{bmatrix} I_{ds} \\ I_{qs} \\ I_{dr} \\ I_{qr} \end{bmatrix} = -([L]^{-1} [R] + [L]^{-1} [\Omega]) \begin{bmatrix} I_{ds} \\ I_{qs} \\ I_{dr} \\ I_{qr} \end{bmatrix} + [L]^{-1} \begin{bmatrix} V_{ds} \\ V_{qs} \\ V_{dr} \\ V_{qr} \end{bmatrix} \quad (7)$$

$$[L]^{-1} = \frac{1}{L_{rr}L_{ss} - L_m^2} \begin{bmatrix} L_{rr} & 0 & -L_m & 0 \\ 0 & L_{rr} & 0 & -L_m \\ -L_m & 0 & L_{ss} & 0 \\ 0 & -L_m & 0 & L_{ss} \end{bmatrix} \quad \begin{matrix} L_{ss} = L_s + L_m \\ L_{rr} = L_r + L_m \end{matrix} \quad (8)$$

$$[R] = \begin{bmatrix} R_s & 0 & 0 & 0 \\ 0 & R_s & 0 & 0 \\ 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & R_r \end{bmatrix} \quad [\Omega] = \begin{bmatrix} 0 & -w_s & 0 & 0 \\ w_s & 0 & 0 & 0 \\ 0 & 0 & 0 & -(w_s - w_r) \\ 0 & 0 & (w_s - w_r) & 0 \end{bmatrix} \quad (9)$$

$$T_g = \frac{3}{2} \cdot p_f \cdot L_m (I_{qs} \cdot I_{dr} - I_{ds} \cdot I_{qr}) \quad P_{gen} = \frac{3}{2} (V_{ds} I_{ds} + V_{qs} I_{qs}) \quad Q_{gen} = \frac{3}{2} (V_{qs} I_{ds} - V_{ds} I_{qs}) \quad (10)$$

Where  $L_s$  and  $L_r$  are the stator and rotor winding inductance,  $R_s$  and  $R_r$  are the stator and rotor winding resistance,  $w_s$  and  $w_r$  are the synchronous and rotor angular speed,  $L_m$  is the mutual inductance,  $I_{ds}$ ,  $I_{qs}$ ,  $I_{dr}$ ,  $I_{qr}$  are the  $d$ - $q$  components of stator and rotor current,  $V_{ds}$ ,  $V_{qs}$ ,  $V_{dr}$ ,  $V_{qr}$  are the  $d$ - $q$  components of stator and rotor voltage and  $P_{gen}$ ,  $Q_{gen}$  are the active and reactive power.

### 3. Control Design

The proposed design consists of applying the LQG optimal control technique to track controlled outputs, taking into account the control actions associated to rotor voltages and pitch angle. In this case, three outputs are desired to control: the angular speed and the active and reactive power.

The general structure of the control system is shown in figure 1a. The control system is made up of a Maximum Power Point Tracking (MPPT) algorithm and the LQG controller to track the optimal reference. A literature survey identifies three common MPPT methods namely, perturbation and observation, wind speed measurement, and power signal feedback. In wind farms, several anemometers are often placed at different locations to measure the average wind speed. If these wind speed information can be properly used in the MPPT process [16]. Therefore, the MPPT algorithm based on wind speed measurement method is considered in this paper. The MPPT algorithm divides the reference space in three regions: Region 1 with maximum power output and variable rotor speed, region 2 with maximum power output and constant rotor speed (smooth transition between region 1 and region 3), and region 3 with constant power output and constant rotor speed.

The state-variable representation of full wind turbine system is achieved by manually manipulating the original system equations and linearizing them. Those equations are highly non-linear in nature. The plant model is obtained by linearizing the equation system via Taylor expansion[17]. In this particular case, the operating point chosen is associated to the wind speed that gives the rated power of the generator.

#### 3.1. LQG Control Design

Supposing the state space equation of the plant is

$$\begin{aligned}\dot{x} &= Ax + Bu + Gw \\ y &= Cx + Du + Hw + \mu\end{aligned}\quad (11)$$

Where  $w$  and  $\mu$  are white noise and used to express the model uncertainty and measured output noise, respectively. Usually,  $w$  and  $\mu$  are considered zero-mean Gaussian stochastic process and independent each other [4, 3].

The basic structure of a LQG controller is shown in figure 1b. The LQG controllers are made up of a Kalman Filter and the multivariate state feedback. The Kalman Filter calculates the estimate of the state vector  $\hat{x}$  based on the sensors measurements and the control model. From observation of figure 1b, it is seen that it is necessary to design the matrices Kalman Filter gain ( $L$ ) and optimal state-feedback ( $K$ ) to get the LQG controller. The separation principle is utilized in the LQG design as a two-step process[12]:

**Step 1.** Obtain the Kalman filter gain matrix ( $L$ ) given by

$$L = P_L C^T R_L^{-1} \quad (12)$$

Where  $P_L$  is given by solution of Algebraic Riccati Equation (ARE):

$$AP_L + P_L A^T + Q_L - P_L C^T R_L^{-1} C P_L = 0 \quad (13)$$

and  $R_L$  is a symmetric definite positive matrix,  $Q_L$  and  $P_L$  are symmetric semi-definite positive matrices.

**Step 2.** Obtain the optimal state-feedback matrix ( $K$ ) given by

$$K = R_K^{-1} B^T P_K \quad (14)$$

Where  $P_K$  is given by solution of ARE:

$$A^T P_K + P_K A + Q_K - P_K B \cdot R_K^{-1} B^T P_K = 0 \quad (15)$$

$Q_K$  and  $P_K$  are symmetric semi-definite positive matrices and  $R_K$  is a symmetric definite positive matrix.

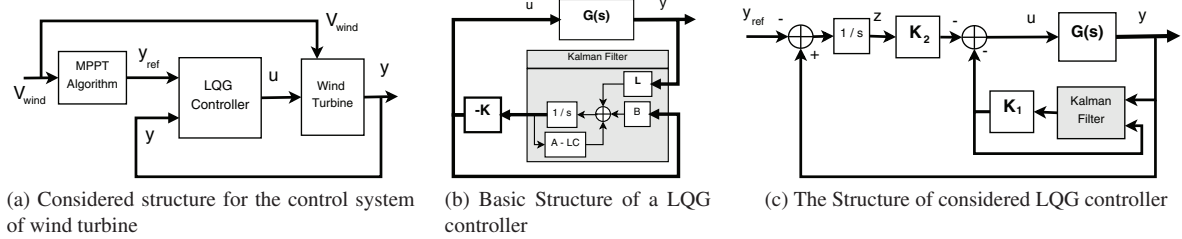


Figure 1: Structure of LQG Controller

In order to ensure an appropriate reference pursuit on the control system, an integrator is added to the LQG control proposed in this paper. The structure of the considered LQG controller with integrator is shown in figure 1c.

For the LQG controller of figure 1c, the Kalman filter gain matrix ( $L$ ) is the same defined above by equation 12, but the optimal state-feedback matrix ( $K$ ) changed, because it is now defined by two matrices  $K_1$  and  $K_2$ . In order to include the dynamic of the integral action in the state space equation 11 and calculated the matrices  $K_1$  and  $K_2$ , the tracking error ( $Z$ ) is adding to the state space, which is defined as the deviation of the wind turbine system output from the corresponding reference signal ( $y_{ref}$ ), from figure 1c and defined by equation 16.

$$\dot{z} = y_{ref} - y \quad (16)$$

The state space equation of the expanded system, including the integral action, is

$$\begin{bmatrix} \dot{x} \\ \dot{z} \end{bmatrix} = A_{new} \begin{bmatrix} x \\ z \end{bmatrix} + B_{new} \begin{bmatrix} u \\ y_{ref} \end{bmatrix} + \begin{bmatrix} G & 0 \\ -H & -I \end{bmatrix} \begin{bmatrix} w \\ \mu \end{bmatrix} \quad (17)$$

$$y = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix} + \begin{bmatrix} D & 0 \end{bmatrix} \begin{bmatrix} u \\ y_{ref} \end{bmatrix} + \begin{bmatrix} H & I \end{bmatrix} \begin{bmatrix} w \\ \mu \end{bmatrix}$$

$$A_{new} = \begin{bmatrix} A & 0 \\ -C & 0 \end{bmatrix} \quad B_{new} = \begin{bmatrix} B & 0 \\ -D & I \end{bmatrix} \quad (18)$$

Then, the optimal state-feedback matrix,  $K = \begin{bmatrix} K_1 & K_2 \end{bmatrix}$ , is given by 14 and 15 replacing  $A$ ,  $B$  by  $A_{new}$  and  $B_{new}$ , respectively.

### 3.2. GA Optimization of Controller

From the above mentioned LQG method design procedure is evident that it is necessary to select four weighting matrices ( $R_L$ ,  $Q_L$ ,  $R_K$ ,  $Q_K$ ) in order to solve the Algebraic Riccati Equations and then get the matrices  $L$  and  $K$ . There are an infinite number of possible selections for the weighting matrices. The trial and error method is typically used in the choice the elements of the weighting matrices to get good performance and robustness. Some methods for selecting the initial point of iteration of the weighting matrices are suggested in the literature [6, 7, 8, 9]. However, none of these methods ensures the optimal selection of weighting matrices and usually several iterations must be performed to find matrices that meet the specified requirements [10]. In this paper a methodology based on Genetic Algorithms is used to automate the search for the best values of the weighting matrices.

To implement GA, a genetic representation of feasible solution, namely individual, and the fitness function to evaluate the candidate solutions are required. The algorithm begins by establishing an initial population of individuals. The individual contains information about the weighting matrices and represent a LQG

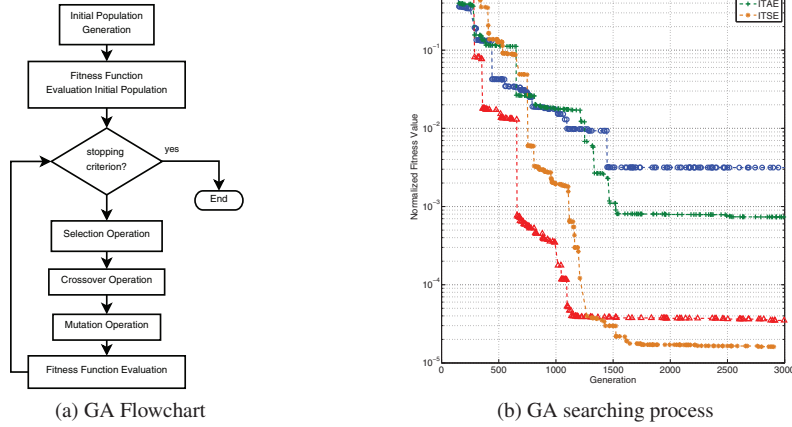


Figure 2: GA Flowchart and Evolution of fitness function

controller. Then, each solution is evaluated to measure its quality by assigning a value equivalent to the performance according to the fitness function. The initial population should be improved through several iterations. In each iteration, three operators, selection, crossover, and mutation, are performed to generate a new population. The Flowchart of the GA is shown in figure 2a.

1) *Individuals*: The genetic representation of a LQG controller is defined by selecting four weighting matrices ( $R_L$ ,  $Q_L$ ,  $R_K$ ,  $Q_K$ ). Diagonal weighting matrices are considered, therefore an individual is composed by twelve elements, namely chromosomes, that correspond to the diagonal elements of the matrices ( $R_L$ ,  $Q_L$ ,  $R_K$ ,  $Q_K$ ). Each chromosome ( $c$ ) has a binary structure with resolution  $nb$  (number of bits). An individual ( $wm_k$ ) based on the weighting matrix information is represented by expression 19.

$$\begin{aligned} individual = wm_k &= \{c_1, c_2, \dots, c_{12}\} \\ chromosome = c_i &= \{b_1, b_2, \dots, b_{nb}\} \end{aligned} \quad (19)$$

2) *Population*: The population structure is defined by expression 20, where  $n_{ind}$  is the amount of individual of a population and each individual ( $wm$ ) is defined by 19. The initial population has a random binary generation model and the population size remains constant in every generation.

$$WM = \{wm_1, wm_2, \dots, wm_{n_{ind}}\} \quad (20)$$

3) *Fitness function*: The most crucial step in applying GA is the choice of the objective functions that are used to evaluate the fitness of each feasible LQG controller. The fitness function is based on the linearized system response to step input, and some optimal performance indices are used for that purpose [18]. Here, four performance indices are considered: Integral of Time multiplied by Absolute Error (ITAE), Integral of Absolute Error (IAE), Integral of the Squared Error (ISE) and Integral of Time multiplied by the Squared Error (ITSE). These performance indices are defined by equation 21, where  $e(t)$  is the error signal in the time domain. The performance indices for the output errors in angular speed, active and reactive power, and also for the input signals (pitch angle and rotor voltages) are calculated. The linearized system is used to get the response and calculate the performance indices in order to avoid the large time-consuming computing of entire system.

$$\begin{aligned} IAE &= \int |e(t)| dt & ISE &= \int (e(t))^2 dt \\ ITAE &= \int t \cdot |e(t)| dt & ITSE &= \int t \cdot (e(t))^2 dt \end{aligned} \quad (21)$$

The fitness function is obtained by sum the performance indices of all signals normalized. Then, four possible fitness functions are obtained, one for each performance index. For example, the fitness function

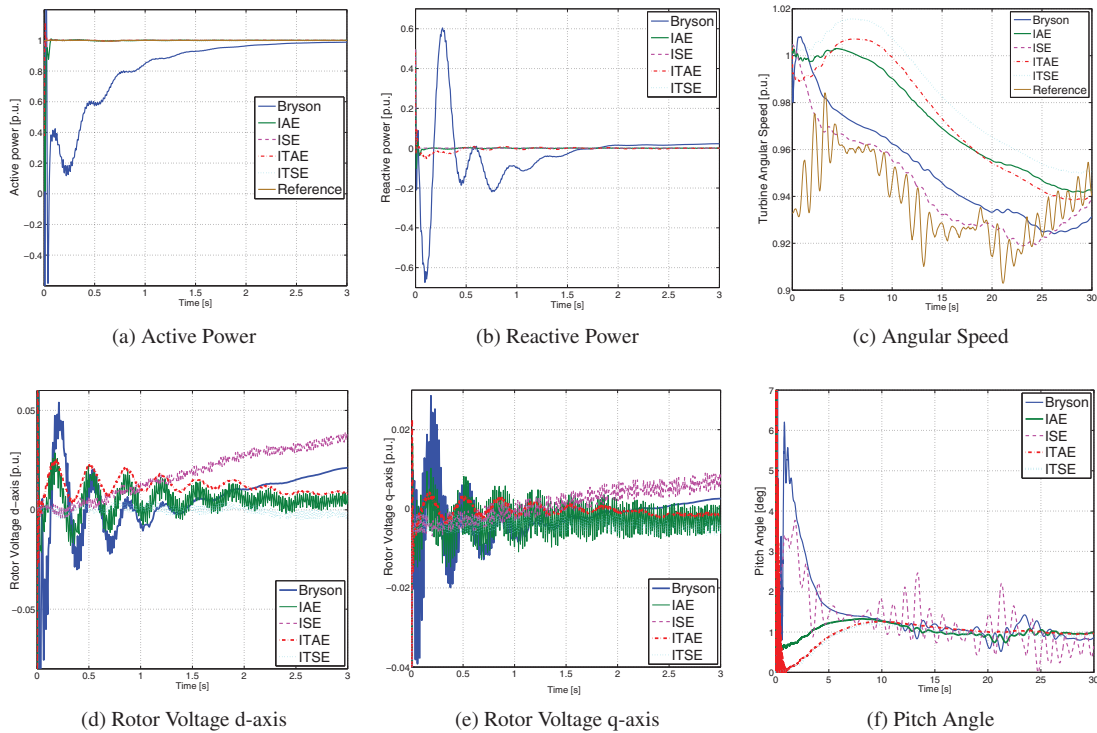


Figure 3: Dynamical system response, LQG-GA method with different performance indices.

defined by performance index IAE is shown in equation 22, where  $\alpha_i$  is a normalization factor of each index. The objective is to find the individual that minimize the fitness function.

$$F_{fitness} = \alpha_1 \int |P - P_{ref}| dt + \alpha_2 \int |Q - Q_{ref}| dt + \alpha_3 \int |w - w_{ref}| dt + \alpha_4 \int |V_{dr}| dt + \alpha_5 \int |V_{qr}| dt + \alpha_6 \int |\beta| dt \quad (22)$$

4) *Selection operation*: The rule known as “roulette wheel selection” is used like selection operator. Basically, the selection operator chooses the best individuals of the current generation, as that the individual with least fitness value has higher probability of selection in the next generation.

5) *Crossover operation*: The crossover operation is to generate new individuals from the ones chosen by selection operator. A crossover between two individuals is performed by selecting two points on the chromosomes of the two individuals and swapping the chromosomes between those points. The selection of the crossover points is random.

6) *Mutation operation*: In this stage, the mutation operator modifies the chromosomes of the individual to generate a new individual. The main characteristic of this operation is to avoid a premature convergence and local optima by generating new individuals which may not be similar to the current individuals. An element of the chromosome is randomly chosen to change. The number of mutated individuals within the population is determined by parameter of GA.

#### 4. Simulation Results

Simulations of the wind turbine have been made in Matlab-Simulink. Table 1 gives the parameters and baseline turbine assumptions used in the simulation to validated the effectiveness of the proposed LQG



Table 1: Parameters and baseline wind turbine assumptions

Wind Turbine and Rotor		Generator	
Blade Radius, R	43.8 [m]	Electrical frequency	50 [Hz]
Number of blades	3	Rated capacity	2 [MW]
Cut-in/cut-out wind speed	4 / 25 [m/s]	Generator inertia	65 [Kg m <sup>2</sup> ]
Gearbox ratio	77	Even number of poles	2
Turbine Inertia	5 · 10 <sup>6</sup> [Kg m <sup>2</sup> ]	High speed s.t. stiffness	10 <sup>5</sup> [Nm/rad]
Low speed s.t. stiffness	114 · 10 <sup>6</sup> [Nm/rad]	High speed s.t. damping	10 <sup>3</sup> [Nms/rad]
Low speed s.t. damping	756 · 10 <sup>6</sup> [Nms/rad]	Stator winding resistance	0.001 [Ω]
Wind Field		Stator winding inductance	0.07 [mH]
Mean wind speed	10.34 [m/s]	Rotor winding resistance	0.0013 [Ω]
Air density	1.225 [Kg/m <sup>3</sup> ]	Rotor winding inductance	0.08 [mH]
Sampling period	0.01 [s]	Mutual inductance	3 [mH]
Turbulence intensity	10%		

controller with GA. The reference values correspond to the following: active power 2 [MW], reactive power 0 [VA] and angular speed 2.05 [rad/s].

Table 2: Performance index for different fitness functions

Fitness function based on	Dinamical model – time=30s				Dinamical model – time=600s			
	IAE	ISE	ITAE	ITSE	IAE	ISE	ITAE	ITSE
IAE	1.2028	0.0703	13.564	0.4883	12.786	0.4261	3669.6	109.09
ISE	<b>0.4855</b>	<b>0.0101</b>	<b>5.6281</b>	<b>0.0520</b>	<b>6.5117</b>	<b>0.0923</b>	<b>1967.6</b>	<b>27.472</b>
ITAE	1.2607	0.1246	14.525	0.5496	12.926	0.4240	3697.4	93.531
ITSE	1.5015	0.0752	18.659	0.8449	<b>11.530</b>	<b>0.3432</b>	<b>3165.6</b>	<b>83.598</b>
Bryson's rule	1.9681	0.5580	15.313	0.3681	19.873	0.9751	5674.2	129.87

The searching process for different fitness function is shown in figure 2b. For the sake of comparison, the fitness values in figure 2b were normalized with the best value of the first generation. It can be observed that the searching process based on ISE and ITSE indices have more deep in the searching from the init value. The following GA parameters were used: a) Population size of 20, b) Crossover rate of 80%, c) Mutation rate of 10%. The algorithm is stopped if maximum number of iterations is exceeded, here 3000, or if no change on the global minimum after occurs 30% of the maximum number of iterations.

A stochastic wind speed has been generated with a mean value of 10.34 [m/s] (the operation point considered to linearization of the system) and turbulence intensity of 10%. The results performance indices values for different controllers are presented in table 2. Each controller (row) is the best controller from the searching process based on each performance index (first column). The results of a controller based on Bryson's rule [7] are presented for reference. From table 2, it can be observed that the best controller is obtained when the fitness function is based on ISE index. In general, all controllers from the searching process present lower values compare with the Bryson's rule controller.

Figure 3 shows the response of the wind turbine controlled system in a stable system condition. Five LQG controllers are considered, one for each performance index. From figure 3, it can be noted that the response transitory for electric variables is improved in all cases compared with the controller based on Bryson's rule.

The controllers based on fitness functions with ISE and ITSE indices are choices to present the results in comparison with other controller based on Bryson's rule [7], all controllers could regulate the system. Fig. 4 shows the time response of the system outputs for the wind profile in long time (600 [s]). The DFIG active power output is presented in Fig. 4a, it can be noticed that controllers based on GA method show a better



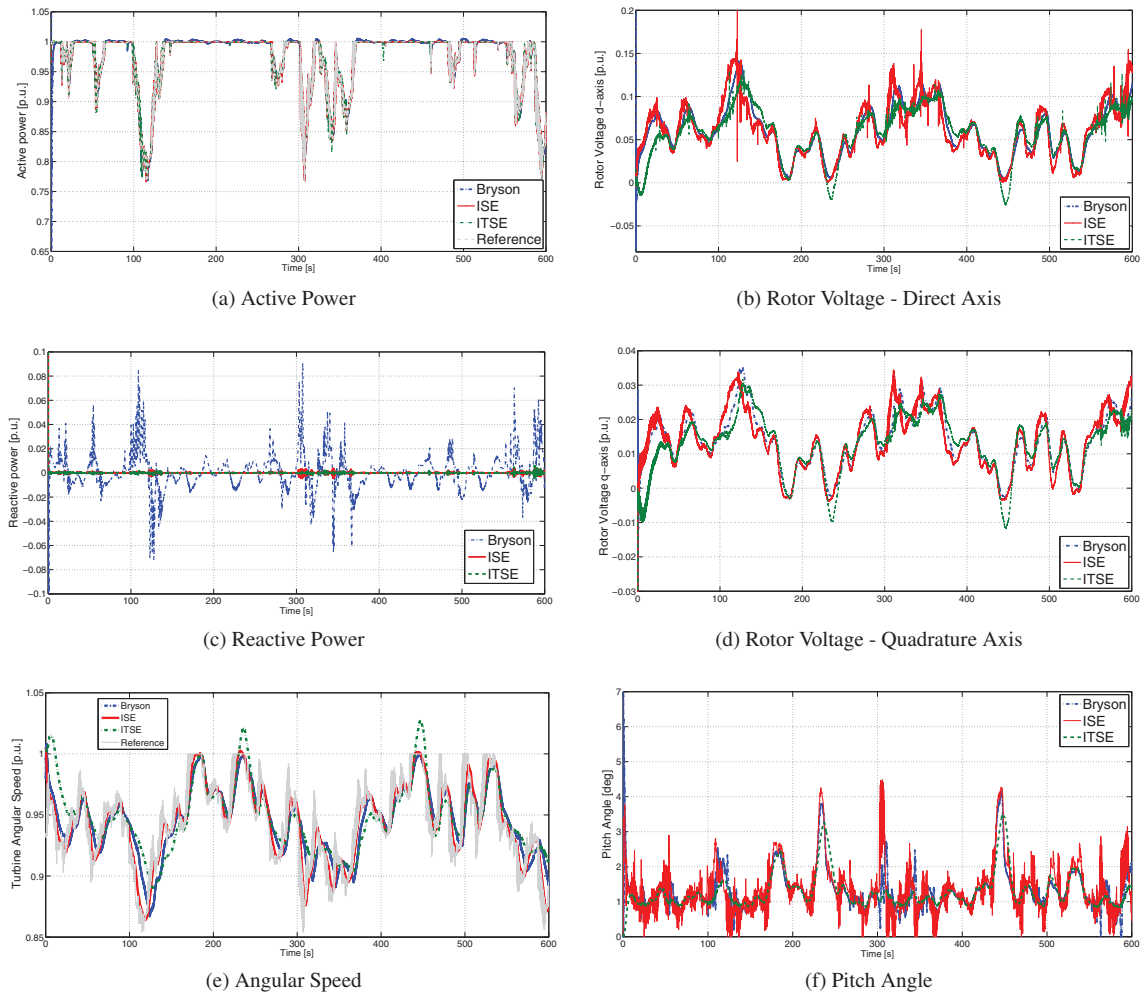


Figure 4: Controlled Outputs and Control Command Signals.

response that the other one based on Bryson's method. It can also be observed that the fluctuations of the active power are directly linked to those of the wind speed.

Fig. 4c exhibit the DFIG reactive power. In that case it is clear that controllers based on GA present lesser fluctuations in response of reactive power that the other one based on Bryson's rule. The DFIG angular speed is depicted in Fig. 4e. For the LQG controller based on ISE index, it can be observed that the tracking of the angular speed reference is the better than the Bryson's rule controller. However, the controller based on ITSE index presents problems when it is necessary to limit the angular speed to the rated value.

Fig. 4b and 4d show the rotor voltage for direct and quadrature axis, respectively. The pitch angle is presented in Fig. 4f. The simulation results validate that the LQG controlled based on GA proposed method has a good follow performance.

## 5. Conclusions

The LQG controller optimal design method based on genetic algorithm, applied to DFIG in wind power system, is proposed in this paper. The methodology based on GA is used to automate the search for the best

values of the weighting matrices in order to get the matrices Kalman Filter gain and optimal state-feedback. The performance index ISE and ITSE are a good alternative to obtain the fitness function to design LQG controllers with GA applied to DFIG wind turbine. The LQG controller optimal design method based on GA is more convenient in practice to design the LQG controller than the conventional trial-and-error method by the simulation results.

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